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Fine-tuning FGD via nonlinear modelling

Nonlinear modelling has helped many industries optimize their processes, but awareness of this technique in the power generation sector is limited. Here, Abhay Bulsari and Jarmo Hagström explain how nonlinear modelling can help cut the material costs for flue gas desulphurization, as successfully demonstrated at the Hanasaari coal fired facility in Finland.

Getting the maximum mileage out of a reactor, boiler or separation equipment is an optimization task that requires detailed quantitative knowledge of its operation. Nonlinear empirical or semi-empirical models that describe the effects of process variables and feed characteristics can summarize this knowledge. New technology to create these models can help production facilities derive more out of their equipment and raw materials at the same time as improving product properties. It is a technology that has become feasible to use in practice. If used effectively, nonlinear modelling can add to a company's competitiveness. It is expensive, but as experience shows time and again, the benefits clearly outweigh the costs. It allows scientists and engineers to perform better process development with less experimentation.

In the case of flue gas desulphurization, a combination of nonlinear models and suitable software can achieve an increase in the efficiency of the process that can cut costs by saving significant amounts of lime. Developing mathematical models of desulphurization processes that are fit for industrial use has always been considered to be too difficult, but the new techniques of nonlinear modelling show it to be feasible. Since these nonlinear models can be quite complicated a simple software tool has been devised that brings these new possibilities within reach of both engineers and scientists.

The nonlinear models for the desulphurization unit at the Hanasaari power plant in Finland show good statistical characteristics, covering about 97 per cent of the variance for sulphur dioxide (SO_2) concentration and 98 per cent of the temperature of the cleaned gas.

PROCESS DEVELOPMENT

Each process development task has different objectives, different variables, different kinds of constraints and different chemical species. The process may be a batch process, a continuous process or a fed-batch one. However, some factors are common to process development of all kinds. In all cases, a product needs to be produced with a given process, from specified raw materials, such that the resulting product properties satisfy certain conditions, typically upper and lower limits. In the case of desulphurization,

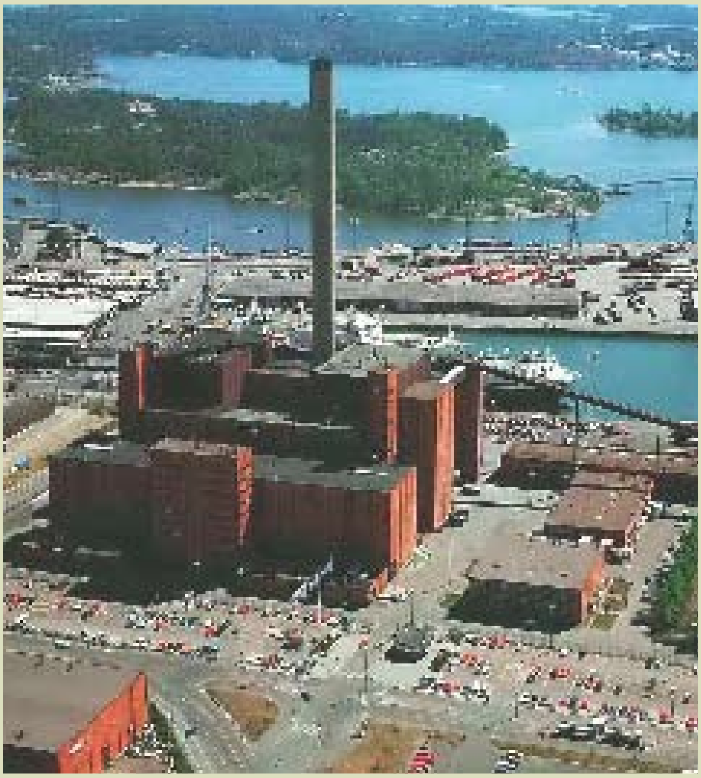
HANASAARI COAL FIRED PLANT, FINLAND

Hanasaari is one of the main power stations that supply the city of Helsinki. The coal fired plant was built in 1977, and has an electricity capacity of 120 MW and a heat capacity of 210 MW.

Its desulphurization unit was built in 1991, and at full capacity it produces 500 kNm^3/h of flue gas from about 60 tonnes/h of coal. The flue gas typically contains between 500-1500 mg/Nm^3 of SO_2, the exact amount depending on the nature of the coal being burnt. Desulphurization of the flue gas consumes hundreds of tonnes of slaked lime per year, and with regulations concerning SO_2 emissions becoming ever stricter desulphurization is an increasingly important part of normal plant operation.

In the semi-dry desulphurization process lime slurry consisting of fresh slaked lime and recycled ash is sprayed into the three-phase reactor from the top. The flue gas enters the reactor near the bottom, and the SO_2 reacts with the lime to form mainly calcium sulphite, which is collected from the bottom as ash. The ash also contains small amounts of unreacted lime and unburnt carbon. Fabric filters remove the dust from the cleaned flue gas.

Operators decide on factors such as the amount of fresh lime to use, the spray power and the fraction of ash to recycle, but they often make those decisions based on their own experience, or according to guidelines given by more experienced operators. This approach rarely delivers optimal operation.



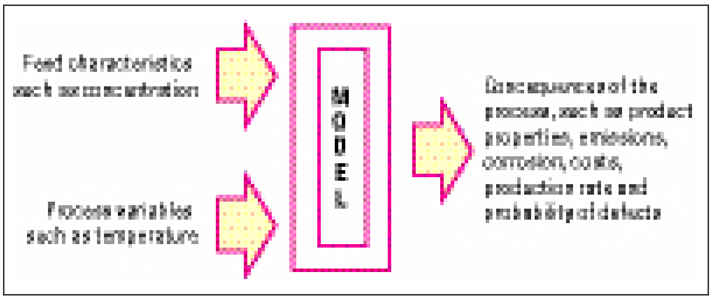


Figure 1: A typical model configuration for process development

the product is flue gas consisting mostly of carbon dioxide and steam, but with a low sulphur content.

The objective of process development is to determine the best values for feed characteristics and process variables to produce product properties that are within desired limits and, preferably, the minimization or maximization of an economic production variable – such as production rate, raw material consumption, energy efficiency, purity, number of defects and emissions.

Sometimes, the feed characteristics are fixed and are not in the hands of the operators, as is the case with the desulphurization process. From the process modelling point of view, the problem seems similar to a wide variety of processes in power generation. Also, feed characteristics and process variables determine the product properties as summarized in Figure 1.

In the case of the desulphurization unit at Hanasaari, the feed characteristics were SO_2 concentration and temperature of the incoming flue gas, the amount of chloride flowing into the reactor measured in terms of chloride content in the ash and the amount of fresh lime in the lime slurry. Process variables include the flow rate of the incoming flue gas and spray power, which determines the velocity and amount of lime slurry sprayed into the reactor. The main objective is to minimize lime consumption while keeping SO_2 emissions below specified limits.

EXPERIMENTAL AND PRODUCTION DATA

The operators at Hanasaari had a positive attitude to process development, and we were able to conduct several experiments there. While normal production data suffice if there is a good amount of variation in the important variables, it is much better to have results from a few systematically planned experiments. In addition to experimental data, some normal operational data were also included in the data set, which was used for model development.

Most of the statistical theory about experiment planning concerns the development of linear empirical models. It is not efficient for the development of nonlinear models, so it is important to keep in mind that while planning experiments their results must be suitable for nonlinear empirical or semi-empirical modelling.

Before model development is attempted, the data are usually analyzed and preprocessed. Figure 2 shows plots from experimental data at Hanasaari for SO_2 concentration and temperature of the cleaned gas against spray power and flow rate of fresh lime milk, while other variables were constant. Both of these process variables reduce the SO_2 concentration and the temperature of the cleaned gas.

NONLINEAR MODELS OF SULPHUR REMOVAL

A large number of models were attempted with different configurations of feed-forward neural networks, with a single hidden layer and with different activation functions. It is often advantageous to transform the input or the

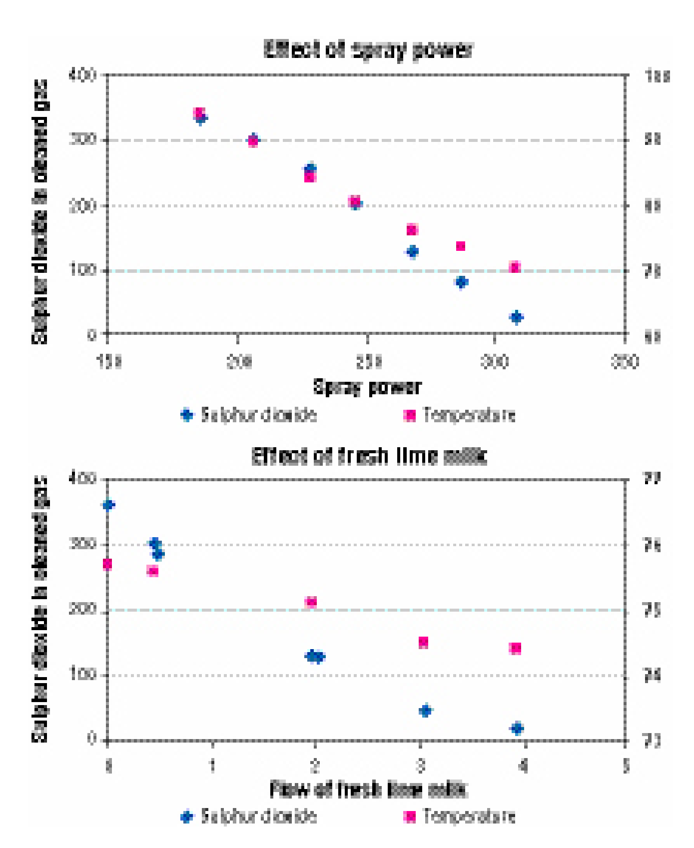


Figure 2: The effect of the spray power (top) and flow rate of fresh lime milk (bottom) on SO_2 concentration and temperature of the cleaned gas

MODELLING TECHNIQUES

Mathematical models put knowledge of the quantitative effects of relevant variables in a concise and accurate form, and can be used instead of experimentation if they are sufficiently reliable. Mathematical models also let the user carry out various kinds of calculations, such as optimization, which can be used to determine suitable values of process variables. This modelling can be performed in various ways, and different ways are suitable in different situations.

It is not possible to use physical modelling in many situations. Even if it is possible, physical models tend to compute output more slowly than empirical or semi-empirical models. Furthermore, development of physical models is time consuming. Although nonlinear modelling tends to be expensive, physical modelling normally costs even more. Physical models involve assumptions and simplifications, while empirical modelling essentially describes the observed behaviour of a system. Thus, empirical modelling is often a better alternative.

Most empirical modelling today is based on linear statistical techniques. Nothing in nature is absolutely linear, so it helps to take nonlinearities into account rather than ignore them. If the range of variables is small, linear techniques are sometimes sufficient. New techniques of nonlinear modelling allow the approximation of nonlinearities without specifying the nonlinearities to be accounted for. They allow for free-form nonlinearities, unlike linear and nonlinear regression methods.

Nonlinear modelling can roughly be defined as empirical or semi-empirical modeling, which takes at least some nonlinearities into account. The models can be static or dynamic. Nonlinear modelling can be performed in many ways, the simpler methods including polynomial regression and linear regression with nonlinear terms. Although, nonlinear regression is useful in some situations, the forms of the nonlinearities have to be specified in these older techniques. The new techniques of nonlinear modelling are based on free-form nonlinearities. They include, for example, series of basis functions, splines, kernel regression and feed-forward neural networks. Feed-forward neural networks are a set of efficient tools for nonlinear modelling, particularly because of their universal approximation capability[1] and form the basis for most applications of nonlinear modelling.

output variables from simple transforms such as logarithms of concentrations to more complicated transforms, even those involving derivatives of variables. Some of the models were trained to predict transformed outputs from the feed-forward neural network using NLS 020 software.

The nonlinear models used at Hanasaari had a low prediction error, which was expected because the data were very good. The root mean square (RMS) error – in simple terms, the standard deviation of the prediction errors – for SO_2 in the cleaned gas was calculated to be 16.12 mg/Nm^3, implying a correlation coefficient of about 97.4 per cent, which is good for an industrial scale process.

As Figure 3 shows, the model predicted the observations quite accurately. The RMS error for the temperature of the cleaned gas was 0.82 °C, which amounts to a correlation coefficient of 97.9 per cent.

The models were implemented in a LUMET system, which consists of software components that allow the facile use of nonlinear models. Figure 4 shows the effects of the flow rate of fresh lime milk and spray power on SO_2 concentration in the cleaned gas for different values of flue gas flow rate and incoming flue gas SO_2 concentration.

At the Hanasaari power plant, the estimated savings derived from the nonlinear models and the LUMET system are expected to be of the order of €90 000 a year.

OPTIMIZATION OF PROCESS CONDITIONS

An advantage of having process knowledge in the form of mathematical models is that it can also be used for optimization. Minimizing operation costs and maximizing production, profitability and quality are all optimization problems. They usually come with constraints of two kinds – equalities and inequalities. All the process variables have to stay within operable limits, which are usually inequality constraints, and several results of operating conditions, such as product properties, are defined by models that are equality or inequality constraints. In mathematical terms, this kind of optimization problem is expressed as

maximize $F(x)$
$x \in R^n$

subject to $c_i(x) = 0$, for $i = 1$ to m
and $c_k(x) \geq 0$, for $k = 1$ to p

In process optimization, the inequality constraints are usually the limits on process variables and possibly also product properties, and are therefore simple inequalities in single variables. Much of the literature describes various techniques for this kind of optimization problem in varying degrees of detail[2].

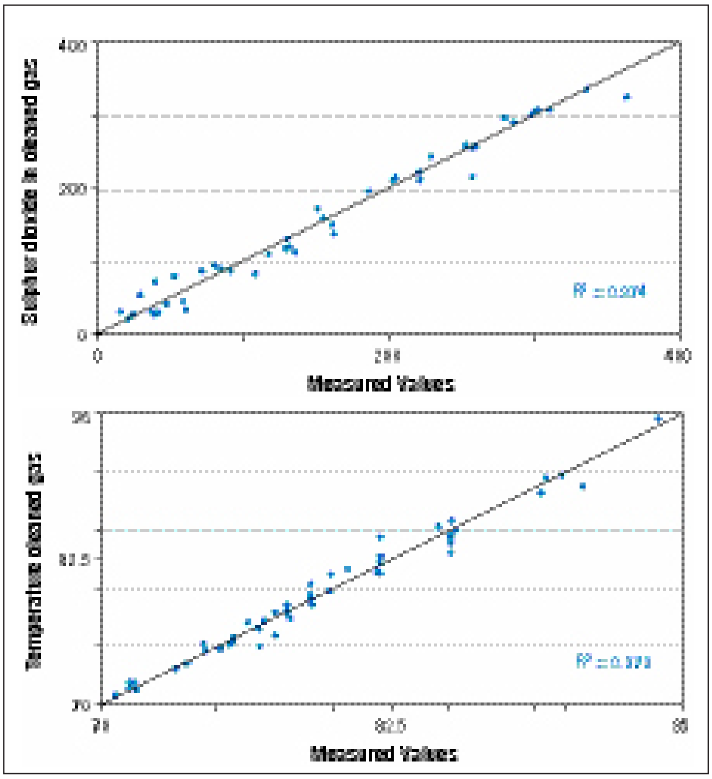


Figure 3: Comparisons of measured and predicted values from the nonlinear models for SO_2 concentration and temperature of the cleaned gas

As previously mentioned engineers and scientists in industry cannot be expected to be familiar with these techniques, so a software tool, called LUMET, has been developed that is easy to use without knowing the details of the methods used in it. Users only need to know what they want to maximize or minimize and the limits on the variables. Sometimes, one may want to determine the process conditions that will result in given product characteristics. This is essentially solving a few equations in several unknowns, which under normal circumstances has an infinite number of solutions. Production personnel are often more interested in determining the conditions under which one of the economic production objectives can be minimized or maximized, while keeping the product properties within acceptable limits.

"At the Hanasaari power plant, the estimated savings derived from the nonlinear models...are expected to be of the order of €90 000 a year"

The limits for the process conditions can also be specified, and one click of the mouse finds the optimum in a few seconds. Let us take an example where the cost of lime consumed is minimized while keeping SO_2 in the cleaned gas below 250 mg/Nm³ and the temperature of the cleaned gas above 72 °C. The LUMET system suggests using 1.259 m³/h of fresh lime milk and a spray power of 275.84 kW, which will keep the SO_2 concentration at the specified limit and the temperature safely above the specified limit. However, it is also possible to make impossible demands in which even constraint satisfaction is impossible. The software then tries to look for the best compromise.

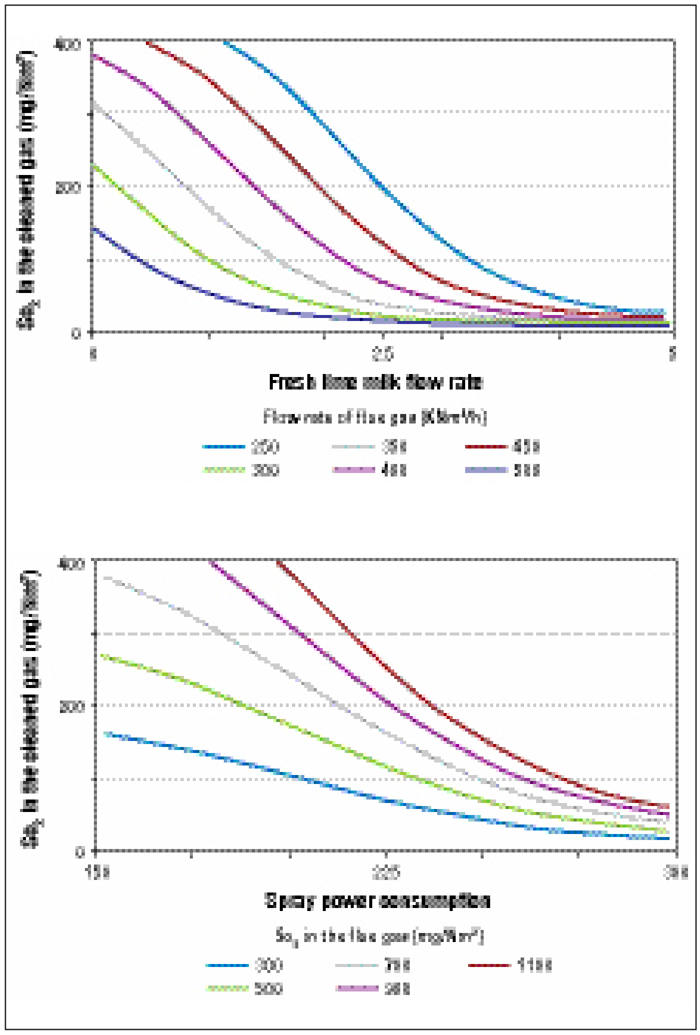


Figure 4: The effect of the flow rate of fresh lime milk on the SO_2 concentration in the cleaned gas for different values of the flow rate of the flue gas (top) and the effect of spray power on the SO_2 concentration in the cleaned gas for different values (bottom)

CONCLUSIONS

By using a combination of nonlinear models and suitable software the efficiency of a coal fired power plant's flue gas desulphurization unit can be increased, resulting in significant savings in the amount of lime consumed.

The same approach with nonlinear semi-empirical modelling can also help improve the combustion efficiency in boilers leading to a significant saving of coal if the right variables are measured.

Thus, nonlinear modelling can make a valuable contribution to the power generation industry. New technologies arise from time to time that affect production economics and open up new possibilities. Thus, companies that embrace new technologies, such as new nonlinear techniques, effectively have a competitive edge over those who do not.

[1]K. Hornik, M. Stinchcombe & H. White, "Multilayer feedforward networks are universal approximators", Neural Networks, Vol. 2 (1989), pp.359-366.

[2]P. E. Gill, W. Murray & M. H. Wright, Practical Optimization, Academic Press, London (1981), pp.136-140.